Sources of Productivity Growth in Health Services: A Case Study of Queensland Public Hospitals

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Abstract: Improving the performance of health sector is one of the most popular issues in Australia. This paper contributes to this important policy debate by examining the efficiency of health facilities in Queensland using the Malmquist Productivity Index (MPI). This method is selected because it is suitable for the multi-input, multi-output, and not-for-profit natures of public health services. In addition, with the availability of panel data we can decompose productivity growth into useful components, including technical efficiency changes, technological changes and scale changes. The results revealed an average of 1.6 per cent of growth in total factor productivity (TFP) among Queensland public hospitals in the study period. The main component contributing to the modest improvement of TFP during the period was catching-up at an average of 1.0 per cent. SFA estimates suggest that the number of nurses is the most influential determinant of output.

I. INTRODUCTION

An analysis of the efficiency of health facilities is important as this sector often consumes a large proportion of budget in many countries. As a result, the efficiency of health care delivery units have been increasingly examined with 80% of the studies published in the last decades

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and the number increase annually (Hollingsworth and Street 2006).

Analysing the efficiency of acute inpatient services is a challenging task due to its multiple inputs and outputs and highly regulated operational environments. One of the most challenging issues when measuring the efficiency of health care service providers is the large number of diseases, and hence large number of outputs. For example, some 700 outputs can be produced by health services using the current system of classification called diagnosis related groups (DRG). One way to overcome this issue is to aggregate the number of outputs using the cost weight of each DRG, measured by the average amount of resources used to produce it. The aggregated output measured this way is also referred to as case-mix, which has been widely used in health governing bodies as a criterion for allocating funds to health service units. However, the number of efficiency studies in Australia, which have used case-mix output are limited to studies by Yong and Harris (1999), Queensland Health (2004) and Productivity Commission (2010). In addition, few previous studies examined the productivity growth and its determinants, which play an important role in improving the performance of the public health system.

This study examines the changes in total factor productivity of public inpatient services in Queensland in the last decade. The remainder of this paper is organised as follows. After this introductory section, the methodology is presented in Section II. Section III describes data sources, choice of variables and descriptive statistics. Empirical results and concluding remarks are presented in Section IV and Section V, respectively.

II. METHODOLOGY

Measuring productivity and efficiency in the health sector is an interesting but challenging task due to its multiple objectives, highly regulated prices, and shortage of information on service quality. This issue can be overcome by using the MPI index, as it does not require information on prices, which may not necessarily reflect the cost of providing services. In addition, the MPI has the ability to decompose the total factor productivity index into changes in technical efficiency and technology. The main limitation of the MPI and other non-parametric approaches is their inability to accommodate noise in the data and provide the statistical properties of the estimates. To mitigate this issue, we apply a bootstrap procedure proposed by Simar and Wilson (1999) to generate confidence intervals for TFP changes, technical efficiency changes and technological changes.[2] We also use stochastic frontier analysis (SFA) to test the robustness of results.

The Malmquist Productivity Index (MPI) was first proposed by Caves *et al*. (1982) using the efficiency notion of Farrell (1957), in which technical efficiency component is based on the distance function measured proposed by Shephard (1953) and Malmquist (1953). In essence, distance functions measure the distance from an actual observation to the technological frontier in an input-output space.

To define the distance functions one must first define the production technology, which is the set of all feasible input-output combinations. Based on the notations described in Coelli

[2] For details of the bootstrap procedure, see Simar and Wilson (1999)

et al. (2005), we define $x \in \mathbf{R}_{+}^{K}$ as a vector of inputs, $y \in \mathbf{R}_{+}^{M}$ as a vector of output, and the production technology T at period t as:

$$T^{t} = (x^{t} / x^{t}) \text{ can produce } y^{t} \tag{1}$$

Using these notations, an input distance function is measured as:[3]

$$D^{t}(x^{t}, y^{t}) = \max \left\{ \theta > 0, (x^{t}/\theta, yt) \in T \right\} \tag{2}$$

Caves *et al*. (1982) defined the MPI of periods t and t+1 as:

$$MPI^{t} = \frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t}(x^{t}, y^{t})} \quad \text{and} \quad MPI^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t}, y^{t})} \tag{3}$$

Changes of the MPI between these two periods, according to Fare *et al*. (1992), are the geometric mean of the abo two indices.

$$\begin{aligned} M^{t,t+1} &= \sqrt{\frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t}(x^{t}, y^{t})} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t}, y^{t})}} \\ &= \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t}(x^{t}, y^{t})} \times \sqrt{\frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^{t}(x^{t}, y^{t})}{D^{t+1}(x^{t}, y^{t})}} \end{aligned} \tag{4}$$

The first component (outside the square root) in equation (4) presents *efficiency changes* or technological progress since it is the ratio of technical efficiency measured by the two frontiers. The first ratio of the component inside the square root of equation (4) represents the distance between the input-output space in period t+1 relative to technologies in periods t and t+1 whilst the second ratio represents distance between input-output of period t relative to technologies of the two periods. Therefore, the second component of the MPI represents *technical changes* between the two periods. As can be seen, the calculation of the MPI and its components between any two periods requires the solving of four linear programming problems to measure the distance functions formed by all combinations of input-output structure and the frontiers at two periods:

$$D_{i,j}(x_{i,j}, y_{i,j}) = \min \left\{ \theta \mid Y_{i,j}\lambda \geq y_{i,j}, X_{i,j}\lambda \geq x_{i,j}\theta, \lambda \geq 0 \right\} \qquad (i, j = t, t+1) \tag{5}$$

where θ is a scalar, λ is a vector of constants, X and Y are matrix of inputs and outputs of all hospitals, respectively, x and y are the inputs and outputs of the hospital being evaluated.

The four linear programming problems in (5) assume constant returns to scale (CRS) those firms on the frontier operate at the most productive scale. The variable returns to scale (VRS) assumption is imposed by adding the additional convexity constraint $N1\lambda$=1 where $N1$ is the vector of ones. Based on CRS and VRS assumptions, many authors further decomposed the

[3] The output distance functions are defined analogously. For more detailed discussions about distance functions, see for example, Coelli *et al*. (2005).

technical changes into *pure efficiency changes*[4] and *scale changes* (Fare *et al*. 1994, Ray and Desli 1997, and Balk 2001). Since the examination of scale changes is still widely debated, this study reports the two most popular decompositions of the MPI into scale changes proposed by Fare *et al*. (1994) and Ray and Desli (1997) for sensitivity analysis. In essence, Fare *et al*. (1994) measures scale changes using CRS and VRS distance functions in each period, while Ray and Desli (1997) use the VRS distance function of all combinations between two periods. The decomposition of Ray and Desli provide a consistent assumption about the production technology but may suffer from infeasible solutions formed by cross-period VRS linear programming problems.

The distance function can be also be used to calculate the MPI and its components using the SFA method (Fuentes *et al*. 2001). Generally, a translog input distance function for the case of K inputs and M outputs is specified as:

$$\begin{aligned}\ln D_{Ii} &= \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + 0.5 \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} \\ &+ \sum_{k=1}^{K} \beta_k \ln x_{ki} + 0.5 \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi} \\ i &= 1, 2, ..., N,\end{aligned} \tag{6}$$

where i denotes the *i-th* firm in the sample and D_{Ii} represents an input distance (time subscripts are dropped for brevity). The application of the SFA technique to distance functions is conducted by introducing a random error component to the distance functions as in equation (6). In addition, the homogeneity of degree one in an input distance function is used to transform it to a relevant format that can be estimated using the SFA method. Recall that a function of homogeneity of degree ω is presented as:

$$D_i(\omega x, y) = \omega D_i(x, y) \text{ for all } \omega > 0 \tag{7}$$

Thus, if we choose one input arbitrarily (e.g., the *k-th*) and replace $\omega = 1/x_K$, this will result in:

$$D_i(x / x_K, y) = D_i(x, y) / x_K \tag{8}$$

Representing the right hand side of the translog input distance function as represented in equation (6) by a brief format of $TL(x,y)$, we have:

$$\begin{aligned}&\ln(D_i / x_{Ki}) = TL(x_i / x_{Ki}, y_i) \\ &\text{or} \\ &-\ln(x_{Ki}) = TL(x_i / x_{Ki}, y_i) - \ln(D_i)\end{aligned} \tag{9}$$

With the introduction of the random error v_i, the transformed translog input-oriented distance function in the final form of equation (9) becomes:

4 Pure efficiency change is defined similar in equation (4) except the VRS technology is assumed.

$$-\ln(x_{Ki}) = TL(x_i / x_{Ki}, y_i) - \ln(D_i) + v_i \tag{10}$$

or

$$\ln(y^*) = \beta_0 + \sum_{i=1}^{5} \beta_i \ln(x_i^*) + 0.5 \sum_{i=1}^{5} \sum_{j=1}^{5} \beta_j \ln(x_i^*) \ln(x_j^*) + \sum_{i=1}^{5} \beta_i \ln(x_i^*) \ln(t) + \beta_t \ln(t) + 0.5\beta_t \ln(t)^2 + v_i - u_i \tag{11}$$

where $\ln(y^*)$=-$\ln(x_{ki})$ and $x^*_i = x_i/x_k$ (i=1,2,3,4) and $x_k^* = y/x_k$

It is shown that equation (11) can be estimated by the SFA method with the composite error term including a non-negative component u_i, representing efficiency, and a random error v_i .

Using this specification, the MPI and its components are measured as:[5]

$$\text{Efficiency Change} = TE^{t+1}/TE^{t} \text{ where } TE^{t}=D^{t}(x^{t},y^{t})=\exp(-u^{t}|(v^{t}-u^{t})) \tag{12}$$

$$\text{Technical change} = \exp\left(0.5\left(\frac{\partial \ln y_t}{\partial_t} + \frac{\partial \ln y_{t+1}}{\partial_{t+1}}\right)\right) \tag{13}$$

$$\text{Scale change} = \exp\left(0.5\sum_{i=1}^{K} \ln(x_i^{t+1}/x_i^t)(\varepsilon_i^t SF_i^t + \varepsilon_i^{t+1} SF_i^{t+1})\right) \tag{14}$$

where $SF_i^t = (\sum_{i=1}^{K} \varepsilon_i^t - 1)\sum_{i=1}^{K} \varepsilon_i^t$ and $\varepsilon_i^t = \frac{\partial \ln y_i^t}{\partial \ln x_i^t}$ $\quad i = 1, 2, ...K$

The applicationa of a SFA method allows us to interpret useful information regarding the contributions of inputs to generate outputs. For example, using mean-corrected data, we can interpret coefficients in SFA results as elasticities at means. The SFA in this study employs a distance function approach, which does not require economic behaviour assumptions such as profit maximisation, hence it is suitable for productivity analyses of public health services. Therefore, the SFA results of this study can be used as a check for the robustness of the DEA results. The formulation of distance function SFA in equation (11) may lead to a difficulty in interpreting the estimated parameters. With only one aggregate output as in this study, we are able to use the parameters of the standard SFA to interpret estimated parameters.

III. DATA

The dataset, collected from various departments in Queensland Health, include financial and operational data of all public health facilities for the period 1996 to 2004. In order reduce the heterogeneity of data, we exclude outpatient clinics, as the scale and scope of services provided by clinics are much different from the inpatient hospital treatment. In addition, new

5 For more details discussions, see Coelli *et al*. (2005, p.300-302)

hospitals are excluded, as their data collection was incomplete. Thus, the final dataset include 35 public hospitals in Queensland.

To avoid the problem of having zero inputs, which can cause difficulties in solving linear programming problems, the labour data, measured in full-time equivalent (FTE), were grouped into four categories: nurses, medical, administrative, and other staff. The capital input was proxied by the number of beds due to the availability of data.

The number of beds can be also be involved in output measure (i.e., number of bed days separations). However, the number of bed itself represents the capacity of hospitals, and hence, can be used as a proxy for capital input. This choice of input variable was made in various pervious health efficiency studies such as Fare *et al.* (1997), Linna (1998), Maniadakis *et al.* (1999), and Blank and Valdmanis (2010). The use of number of beds as a proxy for capital can also avoid possible biases associated with prices, which are subjected to regulations in public health services.

As mentioned previously, the single output variable (i.e., weighted number of episodes) was selected to overcome the difficulty of incorporating some 700 outputs (classified by DRG) in the analysis.[6] Another advantage of using DRG-weighted episodes as output, is that it can capture differences in the quality of clinical services. For example, more weight is given to complicated procedures such as open-heart surgery, which implicitly integrated that these procedures require higher quality services. However, this study does not have the available data to allow an adjustment for any variation in service quality that may exist between hospitals. As noted by Hollingsworth (2003) in his comprehensive review of 188 studies on health care efficiency, lack of data is a common issue. In addition, the quality measures used in some efficiency studies of health services are arguable. For example, Maniadakis *et al.* (1999) used the number of survivals and Productivity Commission (2010) used the mortality rate as a proxy for quality of services. However, using survival rate or mortality rate as a measure of quality would penalise hospitals that admit more severe patients. This issue can be mitigated to some degree by using casemix-adjusted mortality rates. We believe that a better measure of quality would be provided by a comprehensive service quality survey of discharged patients (e.g., SERVQUAL). This measure has previously been used in efficiency studies published by Sola and Prior (2001), Razak (2003), and Pink *et al.* (2003). In addition, a better alternative indicator of service quality than mortality rate is the hospital-acquired complications measured proposed by Mitchell *et al.* (2009). This indicator measures the rate of complications that occurred during the hospitalisation period; unfortunately, we were unable to collect such data for this study.

The descriptive statistics of the dataset, classified by hospitals and districts levels, are presented in *Table 1*. In general, that there is a large difference in the size of health services, reflecting differences in scale of population among different areas. It can also be seen that nurses represent the largest proportion of labour inputs since health services are a labour intensive sector.

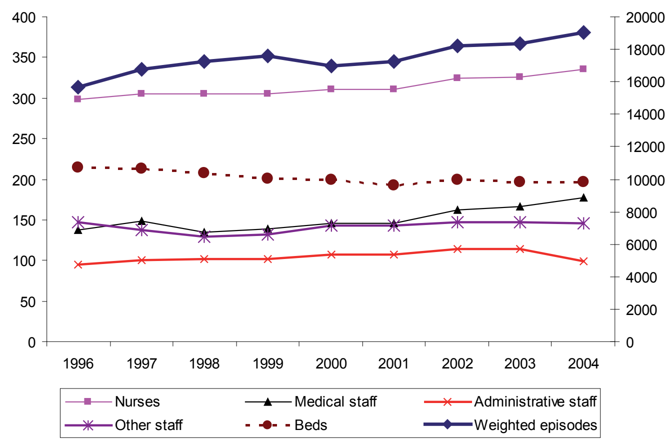
[6] If using the current version of the International Classification of Diseases (ICD-10), the number of outputs will be more than 10 thousands.

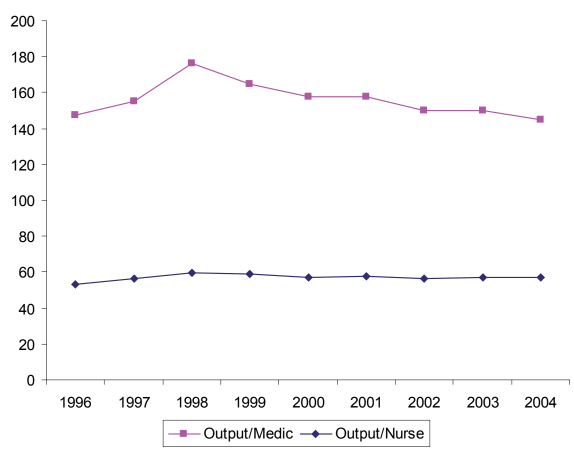
Table 1: Descriptive Statistics

Variables	Mean	Std.	Min	Max
Weighted episodes	17453	19972	776	93906
Nurses	313.21	382.79	23.32	1862.55
Medical staff	150.89	221.25	5.59	1161.49
Administrative staff	104.58	138.56	3.98	725.19
Other staff	141.44	186.48	13.25	1008.83
Number of beds	202.44	217.04	18.00	1138.00

The trend of average inputs and output, presented in *Figure 1*, show a slightly increasing trend in the number of outputs but the levels of inputs used are also increasing slightly with the exception of number of beds. Fortunately, the slope of output trend seems higher than that of inputs. Thus, it is likely that TFP of health services in Queensland will have little change in the study period. Partial productivity measures show little improvement in weighted episodes per nurse whilst the level of output per medical staff increased rapidly in 1996-1998 period then decreases slightly since then.

Figure 1: Trend of Input and Output Levels and Partial Productivity Measure





The results of the MPI suggest that on average, health services in Queensland gained an average of 1.6 per cent per year of TFP in the study period (see *Table 2*), which is as expected from the illustration of the raw data.[7] Overall, we can see that public health services in Queensland experienced slight increase for all years, compared to the reference year in 1996, but only for the years 1997, 1998, 2001 and 2004 was is this increase statistically significant (at 5 per cent). Moreover, none of the two main components (efficiency changes and technical changes) shows significant increase at 5 per cent level. Nevertheless, technical changes are the driving force of productivity growth in Queensland health in the study period with the contribution of 1.4 per cent increase, on average.

Table 2: Average Productivity Growth (95% Confidence Interval are in Brackets)

Years	Efficiency changes	Technical changes	TFP changes
1997	1.088 (0.969, 1.194)	0.978 (0.884, 1.111)	1.064 (1.024, 1.107)
1998	0.937 (0.886, 1.100)	1.139 (0.954, 1.208)	1.067 (1.025, 1.098)
1999	1.030 (0.916, 1.098)	0.977 (0.910, 1.108)	1.006 (0.973, 1.041)
2000	0.994 (0.899, 1.090)	0.962 (0.874, 1.071)	0.956 (0.930, 0.988)
2001	1.130 (0.935, 1.232)	0.898 (0.822, 1.086)	1.015 (1.000, 1.028)
2002	0.812 (0.782, 1.000)	1.232 (0.987, 1.290)	1.001 (0.962, 1.036)
2003	0.986 (0.955, 1.072)	1.024 (0.938, 1.066)	1.010 (0.993, 1.030)
2004	1.077 (0.998, 1.131)	0.943 (0.900, 1.024)	1.016 (1.004, 1.040)
Average	1.002 (0.915, 1.113)	1.014 (0.907, 1.118)	1.016 (0.989, 1.045)

Note: The reference year is 1996. All average figures are geometric means. Confidence intervals are calculated using the bootstrap procedure proposed by Simar and Wilson (1999).

There is very little evidence of growth in technological progress among health services during the study period with an average growth of efficiency at 0.2 per cent. One reason is that the improvement of health technologies often requires very large investment, and hence, is difficult to occur on a yearly basis. In addition, the average figure may show a distorted picture as improvements in productivity in some hospitals maybe counter-balanced by a deterioration in productivity in other hospitals.

[7] Results of this study are produced using the DEAP (Collie, 1996) and FEAR (Wilson, 2008) programs.

Further decomposition of technical changes revealed that pure efficiency produces a major contribution to this component with an average of one per cent despite the bootstrapped confidence interval, which suggests no significant improvement in any year. Both alternative decompositions of scale changes suggest a tiny improvement of scale efficiency with an average of 0.4 and 0.1 per cent, by Fare *et al.* (1994) and Ray and Desli (1997) decompositions, respectively. However, an agreement between the two approaches was only reached in three years: 1998, 2003 and 2004.

Table 3: Further Decomposition of Technical Changes (95% CI are in Brackets)

Years	Pure efficiency changes*,**	Scale changes*	Scale changes**
1997	1.003 (0.874, 1.136)	0.975 (0.871, 1.131)	1.021 (0.914, 1.012)
1998	1.057 (0.889, 1.133)	1.077 (0.954, 1.209)	1.010 (0.924, 1.014)
1999	0.978 (0.883, 1.122)	0.999 (0.903, 1.113)	1.002 (0.938, 1.015)
2000	0.987 (0.894, 1.115)	0.975 (0.870, 1.077)	1.013 (0.928, 1.008)
2001	0.963 (0.899, 1.110)	0.933 (0.835, 1.074)	1.004 (0.955, 1.010)
2002	1.088 (0.886, 1.170)	1.133 (0.980, 1.258)	0.984 (0.921, 1.018)
2003	1.028 (0.930, 1.073)	0.997 (0.939, 1.062)	0.993 (0.954, 1.005)
2004	0.983 (0.932, 1.066)	0.959 (0.900, 1.027)	0.984 (0.931, 0.994)
Average	1.010 (0.898, 1.115)	1.004 (0.905, 1.117)	1.001 (0.933, 1.009)

Note: Decompositions proposed by * Fare *et al.* (1994), and **Ray and Desli (1997). The reference year is 1996. All average figures are geometric means. Confidence intervals are calculated using the bootstrap procedure proposed by Simar and Wilson (1999).

Overall, there are little differences between the estimates of the two decomposition approaches in the remaining years. In addition, the bootstrap results show that most scale changes are not significant. Among the possible reasons suggested by Coelli *et al.* (2005, p. 293),[8] a neutral rate of technical changes among hospital of different sizes may contribute to the similarity of scale

[8] They suggested that the scale changes decomposed by Fare *et al.* (1994) and Ray and Desli (1997) only differ substantively if there are: (1) significant differences in scales among firms in the sample, (2) scale economies, (3) non-neutral rates of technical changes across firms with different sizes.

changes between the two estimates since the descriptive statistics show significant differences in size and it is hard to argue that there is no scale economies in health services.

As mentioned previously, one disadvantage of the distance function SFA is that when choosing one input arbitrarily as a *numéraire* as in equation (11) the estimated parameters are difficult to interpret. Thus, in this section we present the parameters estimated by traditional SFA method as in equation (15) for the ease of interpretation (the estimation of productivity changes is still conducted by distance function SFA).

$$\ln y^t = \beta_0 + \sum_{i=1}^{K} \beta_i \ln x_i^t + 0.5 \sum_{i=1}^{K} \sum_{j=1}^{K} \beta_{ij} \ln x_i^t \ln x_j^t + \sum_{i=1}^{K} \beta_{it} \ln t \ln x_i^t + \beta_t \ln t + 0.5 \beta_{tt} (\ln t)^2 + v^t - u^t \qquad (15)$$

The SFA parameters show that all inputs significantly determined the level of output generated by hospital; with the exception of "other staff" (see *Table 4*). Since the data were mean-corrected for SFA calculation, parameters estimated are interpreted as elasticities at means. For example, the results suggest that one per cent increase in the number of nurses is resulted in 0.68 per cent increased in output, on average. The magnitude of the parameters suggests that the number of nurses is the most influential input, followed by capital and medical staff. The parameter for "other staff" seems counter intuitive as one per cent increase of this input leads to a reduction of 0.32 per cent in output. One possible reason for this is that, on average, hospitals in this study may already employ more "other staff" that the level needed to operate efficiently.

Table 4: Estimates of SFA Production Functions

Coefficients	Estimates	Std. Err.	Coefficients	Estimates	Std. Err.
β_0	***9.382	0.057	β_{25}	0.196	0.163
β_1	***0.679	0.074	β_{2t}	***0.047	0.014
β_2	***0.271	0.042	β_{33}	0.151	0.117
β_3	-0.022	0.047	β_{34}	0.065	0.132
β_4	***-0.321	0.048	β_{35}	**0.383	0.169
β_5	***0.313	0.063	β_{3t}	0.004	0.014
β_{11}	***-1.514	0.404	β_{44}	**-0.494	0.233
β_{12}	***0.644	0.199	β_{45}	-0.32	0.227
β_{13}	**-0.496	0.201	β_{4t}	-0.016	0.016
β_{14}	***1.127	0.277	β_{55}	*-0.455	0.254
β_{15}	0.107	0.287	β_{5t}	-0.003	0.019
β_{1t}	-0.034	0.022	β_t	0.004	0.004
β_{22}	***-0.456	0.171	β_{tt}	***-0.01	0.003
β_{23}	-0.039	0.114	δ^2	***0.036	0.012
β_{24}	*-0.273	0.162	γ	***0.964	0.093
Log likelihood: 133.959			Wald test of overall performance $x^2(27)$=12330, p-value=0.00		

Note: Notations are: y=weighted episodes, X_1=Nurses, X_2=Medical staff, X_3=Administrative staff, X_4=other staff, X_5=Number of beds. Significant levels are: *=10%, **=5%, and ***=1%

The decompositions using distance function SFA method are similar with that of the DEA results regarding efficiency changes. However, it produces lower estimates on technical changes and more positive on scale changes. Nevertheless, the differences between the two estimates are not substantial. For example, the DEA results suggest the average TFP change is 1.6 per cent whilst that of the SFA is 1.2 per cent.

Table 5: MPI Decomposition of SFA Results

Years	Efficiency change	Technical Changes	Scale changes	TFP Changes
1997	0.978	0.961	1.078	1.013
1998	0.961	0.969	1.258	1.171
1999	1.032	0.976	0.885	0.891
2000	1.035	0.981	1.070	1.086
2001	0.994	0.987	0.984	0.965
2002	1.031	0.993	1.063	1.088
2003	0.991	0.999	1.036	1.025
2004	0.999	1.005	0.887	0.890
Average	1.002	0.984	1.027	1.012

Note: The reference year is 1996. All average figures are geometric means.

V. CONCLUDING REMARKS AND SUGGESTIONS

This study has analysed the growth of productivity in Queensland Health Services in the last decades using the MPI method. Based on the availability of data, the analysis selected one output (weighted episodes) and five inputs: number of nurses, medical, administrative and other staff, and number of available beds. The results revealed an improvement in TFP with an average of 1.6 per cent per year in the study period. In addition, the most important component of contributing to productivity growth was technical efficiency changes, followed by scale changes. There is little evidence of technological changes and scale improvement among hospitals in the study period. It is possible that large investment for new medical technology and neutral technological changes among hospital of different sizes contribute to these issues.

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